

## Interactive Image Segmentation and Edge Detection of Medical Images

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### Abstract

*In computer vision and object recognition, effective and efficient image segmentation is an important task. This paper presents an Interactive Segmentation of Medical Images. Since fully automatic image segmentation is usually very hard for natural and medical images, interactive schemes with a few simple user inputs are good solutions. The users only need to roughly indicate the location and region of the object and background by using strokes, which are called markers. For Interactive Segmentation, maximal similarity based region merging algorithm is used. Secondly, an auto adaptive Edge-Detection algorithm is used to detect the edges. Compare to other edge detection algorithm (Sobel, Prewitt, Canny, Laplacian), an autoadaptive is efficient and robust.*

### Keywords

*Image segmentation, Region merging, Maximal Similarity, Edge Detection.*

### 1. Introduction

Despite many years of research, unsupervised image segmentation techniques without human interaction still do not produce satisfactory results. Fully automated segmentation is an ill-posed problem due to the fact that there is neither a clear definition of a correct segmentation nor an objective measure of the goodness of a segment [1],[2]. Therefore, semi-automatic segmentation methods incorporating user interactions have been proposed [3],[10],[11],[12],[19] and are becoming more and more popular. In order to do a semantically meaningful image segmentation

it is essential to take a prior information about the image into account. Such information, for example can be provided by the user through a set of strokes labeling the pixels in an image. This issue has been addressed in the literature as interactive image segmentation, which has been successfully used in snake[3], intelligent scissors[4] and interactive graph-cut[5]. In this paper, maximal similarity based algorithm is used for interactive image segmentation. Initial segmentation is performed using mean shift algorithm. The interactive information is introduced as markers, which are input by the users to roughly indicate the position and main features of the object and background. The MSRM algorithm is used to calculate the similarity of different regions and merge them based on the maximal similarity rule with the help of markers. The object is separated from the background when the merging process ends.

The second step in this paper is edge detection of separated object. Edge detection has become an important task in medical field. A medical image is always influenced by the different kinds of noises, image errors and human factors, so the edges of medical images are not clear, it is difficult to accurately determine by the human eyes. The edge detection is done by autoadaptive edge detection algorithm. Compare to other edge detection algorithm, an autoadaptive algorithm detects the complete, continuous and detailed edges. The rest of the paper is organized as follows. Section 2 describe maximal similarity based merging algorithm. Section 3 gives an autoadaptive edge detection algorithm. Section 4 performs experiments on different images. Section 5 conclude the paper.

### 2. Maximal similarity based region merging

Initial segmentation is done using mean shift algorithm [6], [7]. After mean shift, many small regions are available. In the interactive image segmentation, the user will mark some regions as object and background regions. The key issue in region merging is how to determine the similarity between unmarked regions with the marked regions so that the similar regions can be merged with some logic control. The similarity measure between two

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regions R and Q defined by Bhattacharyya coefficient [8], [9], [13]-

$$\rho(R, Q) = \sum_{u=1}^{4096} \sqrt{Hist_R^u} \cdot Hist_Q^u \quad (1)$$

Where  $Hist_R$  and  $Hist_Q$  are the normalized histograms of R and Q, respectively, and the superscript  $u$  represents the  $u^{th}$  element of them. Bhattacharyya coefficient is a divergence-type measure which has a straight forward geometric interpretation. It is the cosine of the angle between the unit vectors

$$and \quad \left( \sqrt{Hist_R^1}, \dots, \sqrt{Hist_R^{4096}} \right)^T$$

$$\left( \sqrt{Hist_Q^1}, \dots, \sqrt{Hist_Q^{4096}} \right)^T$$

The higher the Bhattacharyya coefficient between R and Q is, the higher the similarity between them is.

### 2.1 Merging rule:

Let Q be an adjacent region of R and denote by  $SQ = \{SiQ\} i=1,2,\dots,q$  the set of Q's adjacent regions. The similarity between Q and all its adjacent regions,

i.e.  $\rho(Q, SiQ), i=1,2,\dots,q$

are calculated. Obviously, R is a member of SQ. If the similarity between R and Q is the maximal one among all the similarities  $\rho(Q, SiQ)$ , we will merge R and Q. The following merging rule is defined [14]: Merge R and Q, if  $\rho(R, Q) = \max \rho(Q, SiQ) \dots (2)$

### 2.2 Merging Algorithm:

Input: the initial mean shift segmentation result.

Output: the final segmentation map.

While there is region merging in the last loop

Stage 1. Merging non marker regions in N with marker background regions in MB

Input: the initial segmentation result or the merging result of the second stage.

(1-1) For each region  $B \in MB$ , form the set of

(1-2) its adjacent regions  $SB = \{Ai\} i=1,2,\dots,r$ .

(1-2) For each  $Ai$  and  $Ai \in MB$ , form its set of adjacent regions  $SAi = \{Sj\} j=1,2,\dots,k$ . There is  $B \in SAi$

Calculate  $\rho(Ai, Sj)$ . If  $\rho(Ai, B) = \max_{j=1,2,\dots,k} \rho(Ai, Sj)$

then  $B = B \cup Ai$ . Otherwise, B and Ai will not merge.

(1-3) Update MB and N accordingly.

(1-4) If the regions in MB will not find new merging regions, the first stage ends. Otherwise go back to (1-1).

Stage 2. Merging non-marker regions in N adaptively

Input: The merging result of the first stage.

(2-1) For each region  $p \in N$ , form the set of its adjacent region  $Sp = \{Hi\} i=1,2,\dots,p$ .

(2-2) For each  $Hi$  that  $Hi \in MB$  and  $Hi \in Mo$  form its set of adjacent regions  $SHi = \{Sj\} j=1,2,\dots,k$ . There is  $p \in SHi$ .

(2-3) Calculate  $\rho(Hi, Sj)$ .  
If  $\rho(P, Hi) = \max_{j=1,2,\dots,k} \rho(Hi, Sj)$ , then  $P = P \cup Hi$ . Otherwise, P and Hi will not merge.

(2-4) Update N.

(2-5) If the regions in N will not find new merging region, the second stage stops. Otherwise, go back to (2-1).

End

## 3. Edge-Detection Algorithm

The second part of this paper gives edge detection of separated object. An edge may be defined as the border between block of different colors or different gray levels [15]. Mathematically, the edges are represented by first- and second-order derivatives. The first-order derivative (i.e., gradient) of a 2-D function  $f(x,y)$  is defined as vector [16]

$$E \quad \nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

Where  $G_x$  and  $G_y$  are the gradient in the x and y coordinates, respectively. The magnitude of the vector is given by

$$mag(\nabla f) = \sqrt{G_x^2 + G_y^2}$$

$$= \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

The angle  $\alpha$  at which the maximum rate of change occurs is

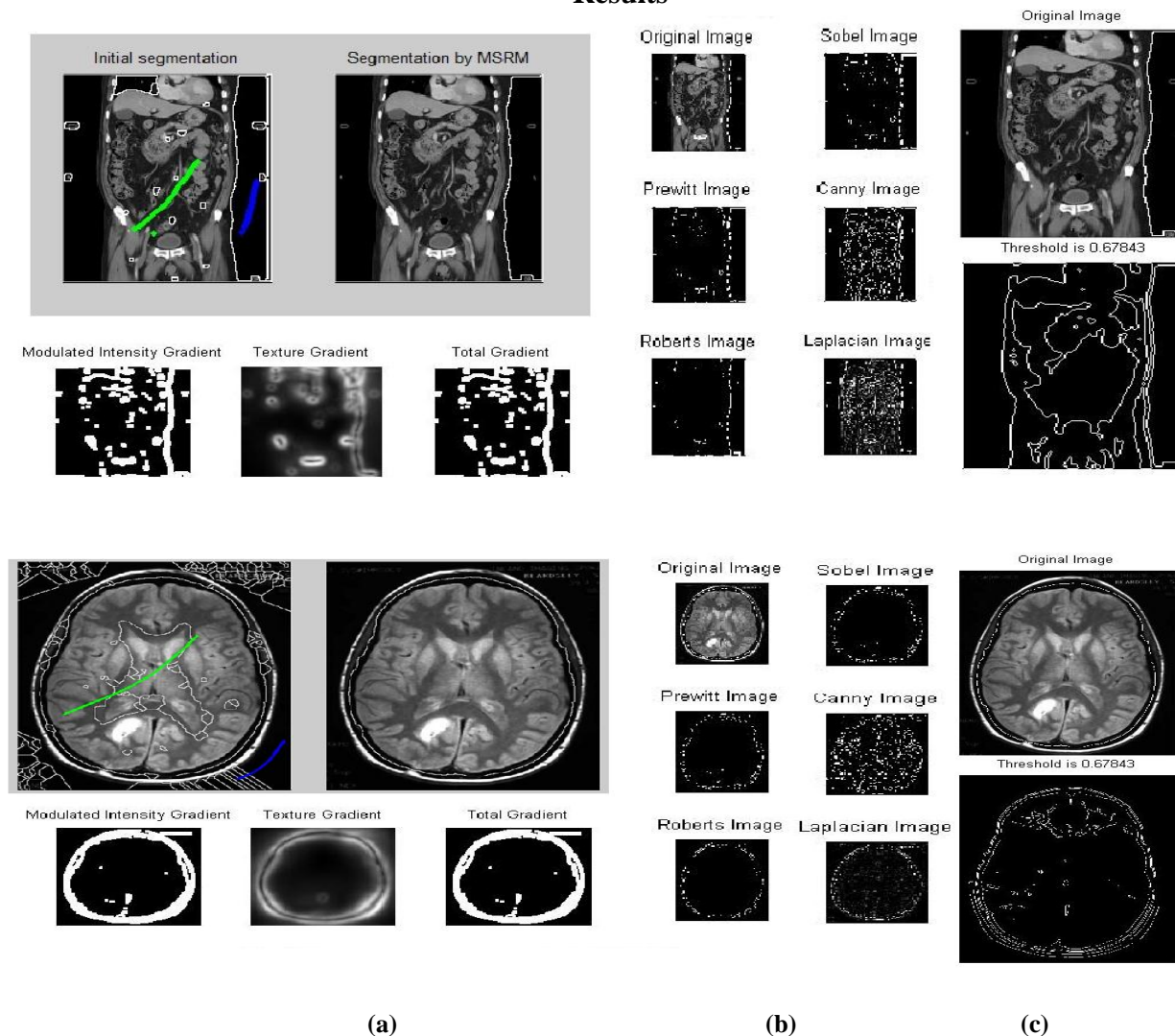
$$\alpha(x, y) = \tan^{-1} \left( \frac{G_x}{G_y} \right)$$

Generally, the variance of the gray level is calculated with one of these edge-detection operators or kernel operators. The slopes in the x- and y-directions are combined to give the total value of the edge strength. The edge-detection operator is then calculated by forming a matrix centered on a pixel chosen as center of the matrix area. If the value of this matrix area is above a given threshold, then the middle pixel is classified as an edge [17].

The edge detection methods that have been published may be grouped into two categories according to the computation of image gradient, i.e., the first-order and second-order derivatives. In the first category, edges are detected through computing a measure of edge with a first-order derivative expression.

Examples of gradient-based edge-detection operators include Roberts, Prewitt, and Sobel operators [17]. The Canny edge-detection algorithm [18], an improved method using the Sobel operator, known to be a powerful edge-detection method. In the second category, edges are detected by searching a second order derivative expression over the image, usually the zero crossing of the Laplacian or nonlinear deferential expression. The following flowchart Fig.1 illustrates steps of the autoadaptive edge detection algorithm [15].

## Results



**Fig.2 (from left to right) a. Interactive segmentation using maximal similarity based algorithm, b. Edge detection using different edge detection operators, c. Edge detection using auto adaptive algorithm.**

#### 4. Conclusion

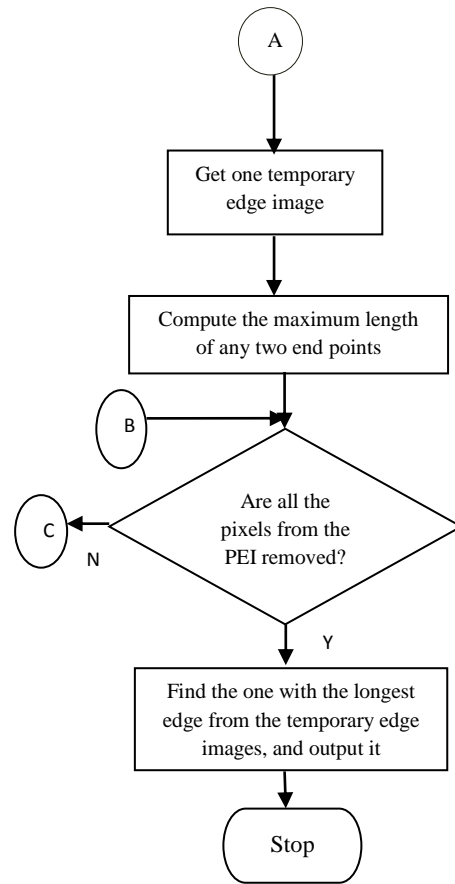
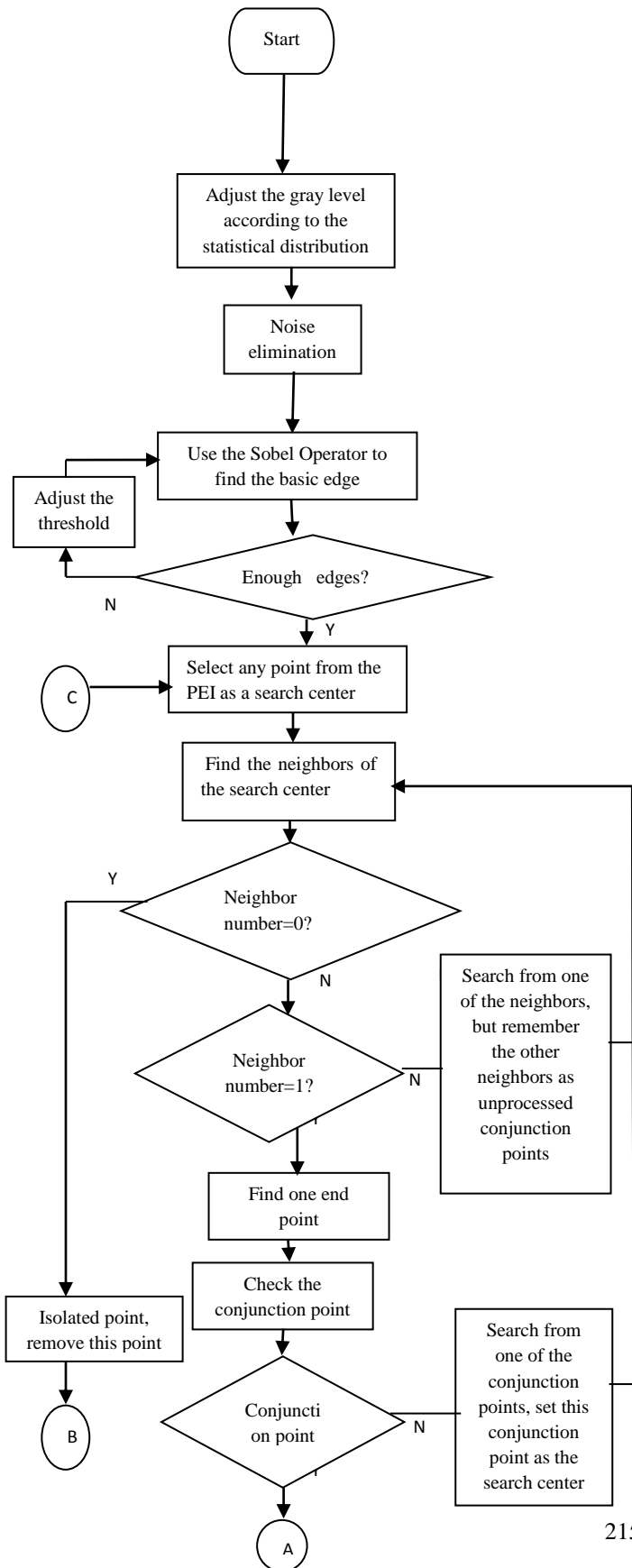
In this paper, interactive image segmentation of medical image is done using maximal similarity based algorithm. The image is initially segmented by mean shift segmentation and the users only need to roughly indicate the main features of the object and background using some strokes, which are called markers. This method is simple and powerful and it gives a general framework for region merging. The edges of separated object are detected using autoadaptive edge detection algorithm. This algorithm is effective and identifies the edges of irregular parts. The edges detected are clear and regular comparatively with other edge detection techniques. These results can be used to analyze the medical image.

#### References

- [1] L. Ding, A. Yilmaz, Interactive image segmentation using probabilistic hypergraph, *Pattern Recognition*, 43, Nov (2010) 1863-1873.
- [2] L. Ding, A. Yilmaz, R. Yan, Interactive image segmentation using Dirichlet process multiple view learning, *IEEE Transaction on image processing*, VOL.21, NO. 4, April (2012).
- [3] M. Kass, A. Witkin, D. Terzopoulos, Snake: active contour models, *International Journal of Computer Vision* 1 (4) (1987) 321-331.
- [4] E.N. Mortensen, W. A. Barret, Intelligent scissors for image composition, in: *Annual Conference on Computer Graphics and Interactive Techniques SIGGRAPH*, (1995), pp. 191-198.
- [5] Y. Y. Boykov, G. Funka-lea, Graph cuts and efficient n-d image segmentation, *International journal of Computer Vision* 70(2) (2006) 109-131.
- [6] Y. Cheng, Mean shift, mode seeking, and clustering, *IEEE Transaction on Pattern Analysis and Machine Intelligence* 17 (8) (1995) 790-799.
- [7] D. Comaniciu, P. Meer, Mean shift: a robust approach toward feature space analysis, *IEEE Transactions on Pattern Analysis and Machine Intelligence* 24 (5) (2002) 603-619.
- [8] T. Kailath, The divergence and Bhattacharyya distance measure in signal selection, *IEEE Transaction on Communication Technology* 15 (1) (1967) 52-62.
- [9] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, second ed., Academic Press 1990.
- [10] F. Meyer, Seucher, Morphological Segmentation, *Journal of Visual Communication and Image Representation* 1 (1) (1990) 21-46.
- [11] P. Felzenszwalb, D. Huttenlocher, Efficient graph-based image segmentation, *International Journal of Computer Vision* 59 (2) (2004) 167-181.
- [12] Q. Yang, C. Wang, X. Tang, M. Chn, Z. Ye, Progressive cut: an Image cutout algorithm that models user intentions, *IEEE Multimedia* 14 (13) (2007) 56-66.
- [13] D. Comaniciu, V. Ramesh, P. Meer, Kernel-based object tracking, *IEEE Transaction on Pattern Analysis and Machine Intelligence* 25 (5) (2003) 564-577.
- [14] J. Ning, Lei Zhang, D. Zhang, Interactive image segmentation by maximal similarity based region merging, *Pattern Recognition* 43 (3) (2009) 445-456.
- [15] T. Qiu, Y. Yan, An autoadaptive edge detection algorithm for flame and fire image processing, *IEEE Transactions on instrumentation and measurement*, VOL. 61, NO. 5, May 2012.
- [16] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 2<sup>nd</sup> ed. Englewood Cliffs, NJ: Prentice-Hall, 2002.
- [17] D. Ziou and S. Tabbone, "Edge detection techniques: An overview," *Int. J. Pattern Recognition. Image Anal.*, Vol 8 no:4, pp.537-559, 1998.
- [18] J. Canny, "A computational approach to edge detection", *IEEE Trans. Pattern Anal. Mach. Intell.* Vol. PAMI-8, no.6, pp. 679-698, Nov. 1986.
- [19] A. Blake, C. Rother, M. Brown, P. Perez, P. Torr, Interactive image Segmentation using an adaptive GMMRF model, in: *Proceeding of the European Conference on Computer Vision*, 2004, pp. 428-441.



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**Fig. 1. Flowchart for autoadaptive Edge detection algorithm**